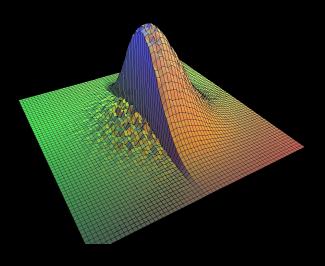
Fast Bilateral Filtering for the Display of High-Dynamic-Range Images

Frédo Durand & Julie Dorsey Laboratory for Computer Science Massachusetts Institute of Technology

Contributions

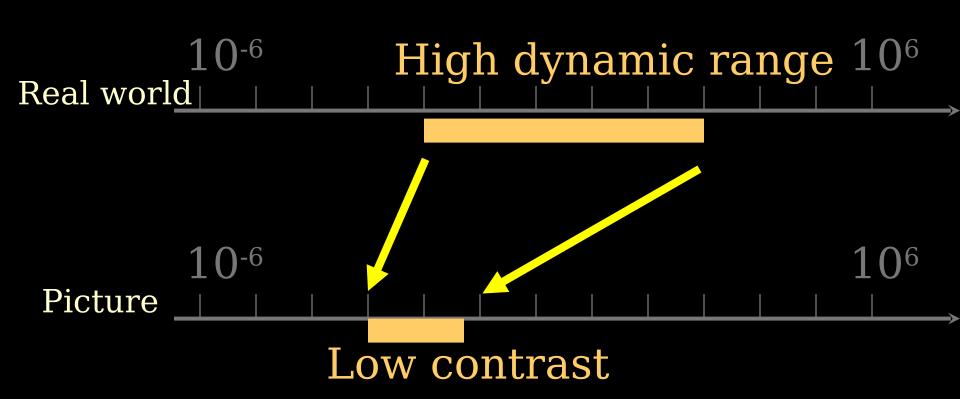
 Contrast reduction for HDR images • Edge-preserving filter





Contrast reduction

- Match limited contrast of the medium
- Preserve details



A typical photo

- Sun is overexposed
- Foreground is underexposed



Gamma compression

• X -> X^y

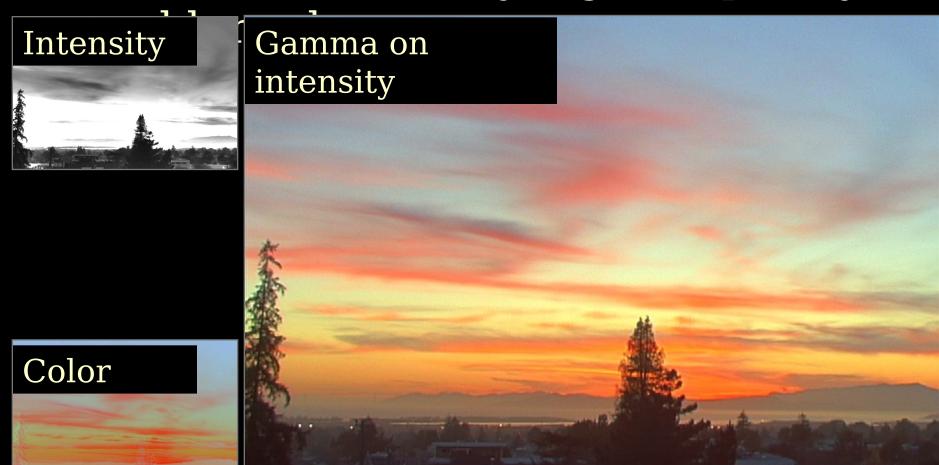
Colors are washed-out





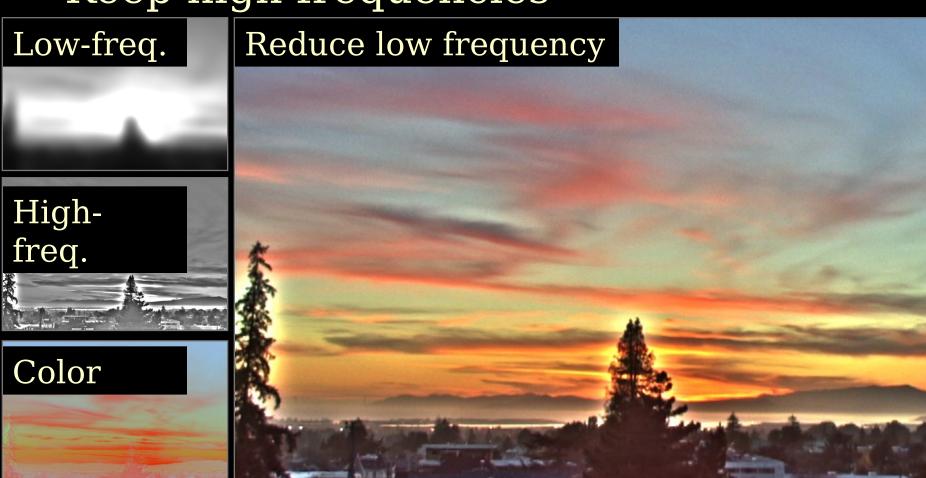
Gamma compression on

intensity high-frequency)



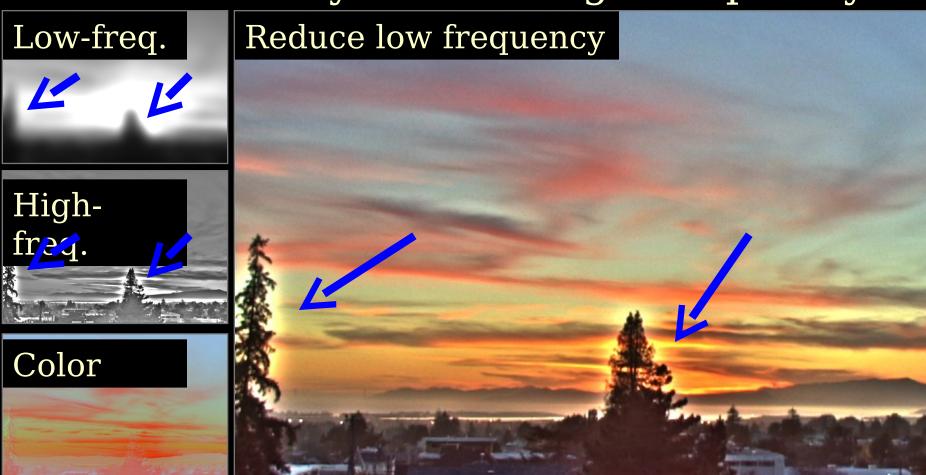
Chiu et al. 1993

- Reduce contrast of low-frequencies
- Keep high frequencies



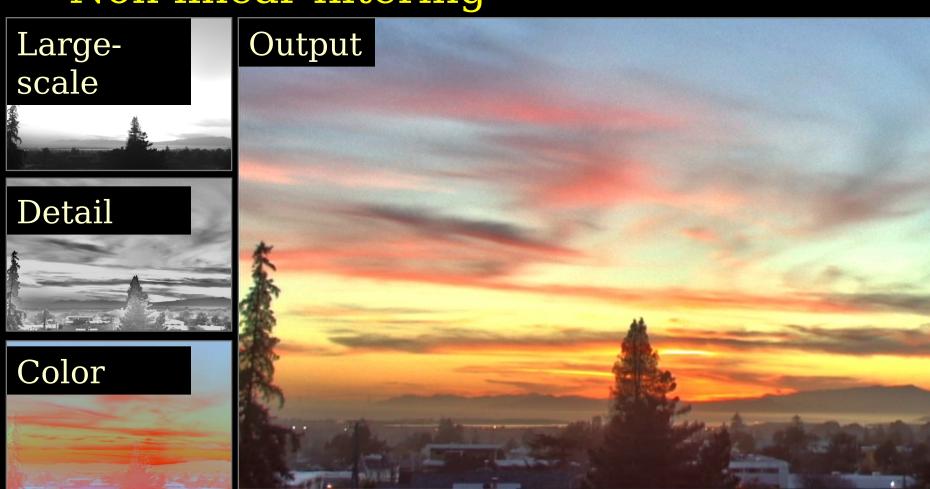
The halo nightmare

- For strong edges
- Because they contain high frequency



Our approach

- Do not blur across edges
- Non-linear filtering



Multiscale decomposition

• Multiscale retinex [Jobson et al. 1997]









Compresse

Compresse

Compresse

• Perceptual filters [Pattanaik et al.

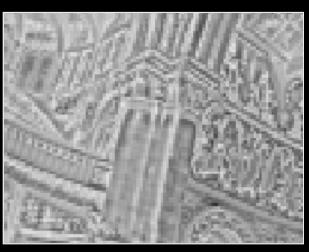


Edge-preserving filtering &

Land Bolin & Turk 1999]

 Multiscale decomposition using LCIS (anisotropic diffusion)







Simplified (at multiple scales)

Compressed

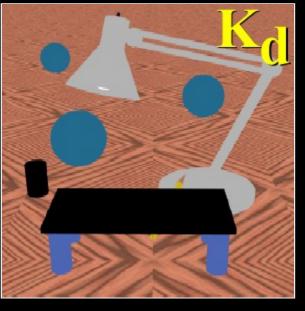
Detail s

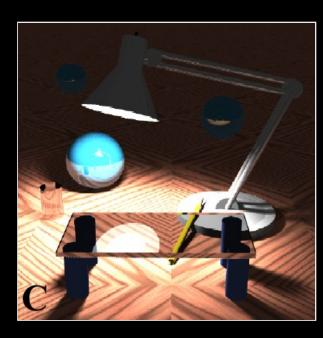
Output

Layer decomposition

- [Tumblin et al. 1999]
- For 3D scenes
- Reduce only illumination layer







Illumination layer Compressed

Reflectance layer

Output

Comparison with our

amplisacing 2 scales

- Can be seen as illumination and reflectance
- Different edge-preserving filter from LCIS







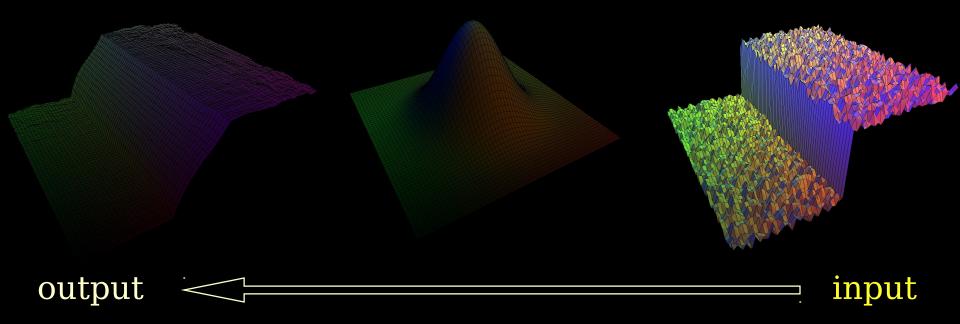
Compressed

Plan

- Review of bilateral filtering [Tomasi and Manduchi 1998]
- Theoretical framework
- Acceleration
- Handling uncertainty
- Use for contrast reduction

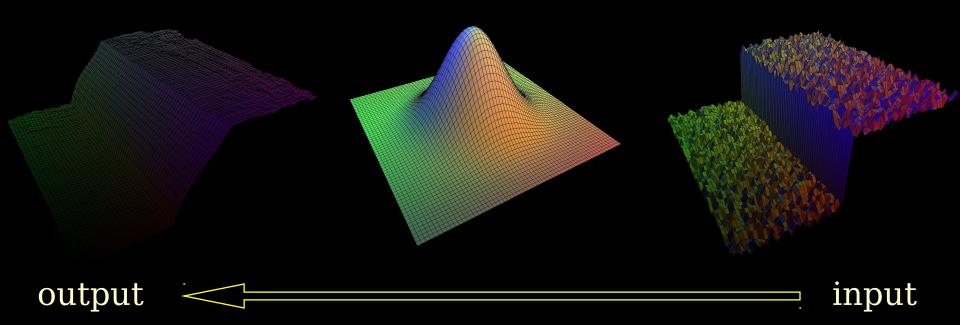
Start with Gaussian filtering

• Here, input is a step function + noise



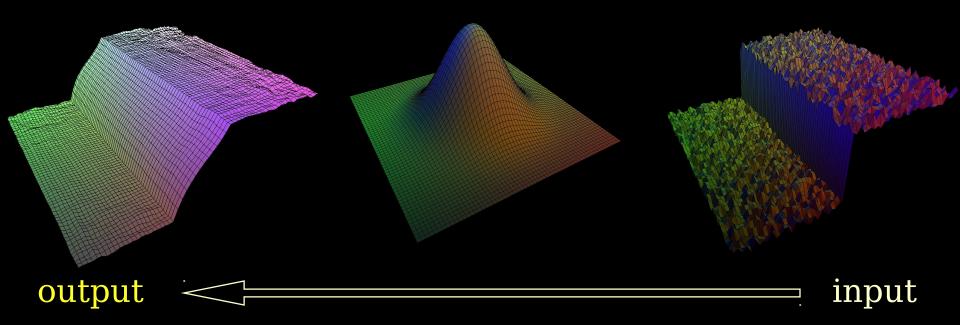
Start with Gaussian filtering

Spatial Gaussian f



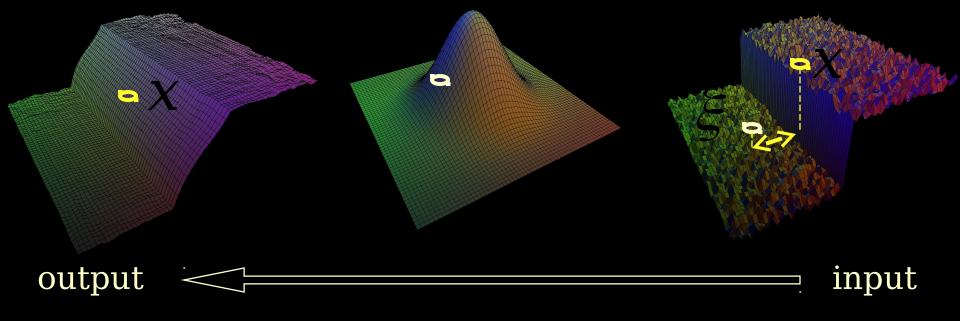
Start with Gaussian filtering

Output is blurred



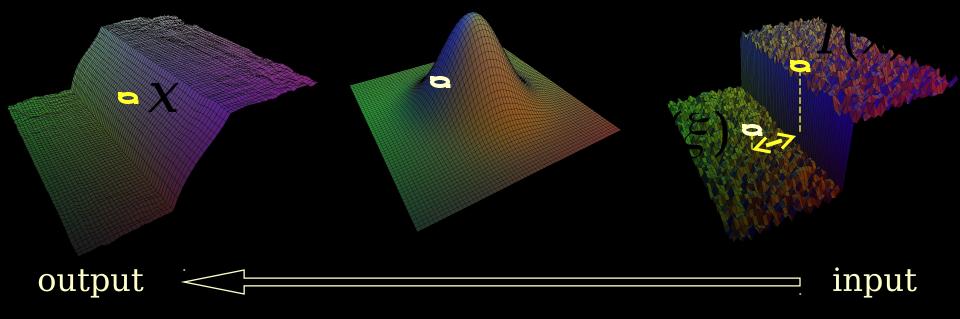
<u>Gaussian filter as weighted</u>

e Weight ξ depends on distance to x



The problem of edges

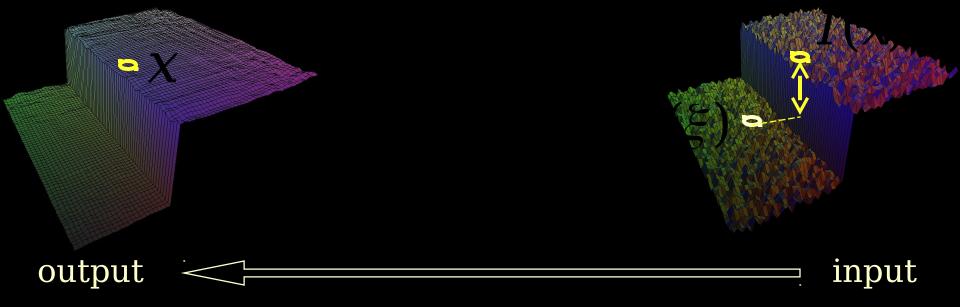
- Here, "pollutes" our estimate J(x)
- It is too different



Principle of Bilateral filtering

[Tomasi and Manduchi 1998]

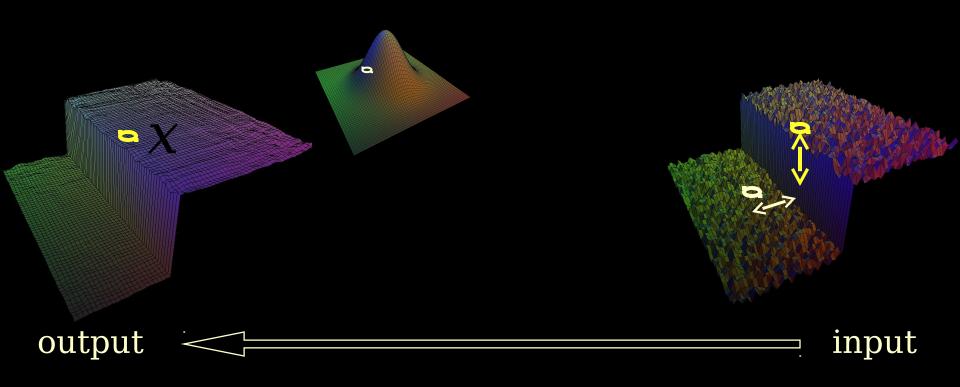
Penalty g on the intensity difference



Bilateral filtering

[Tomasi and Manduchi 1998]

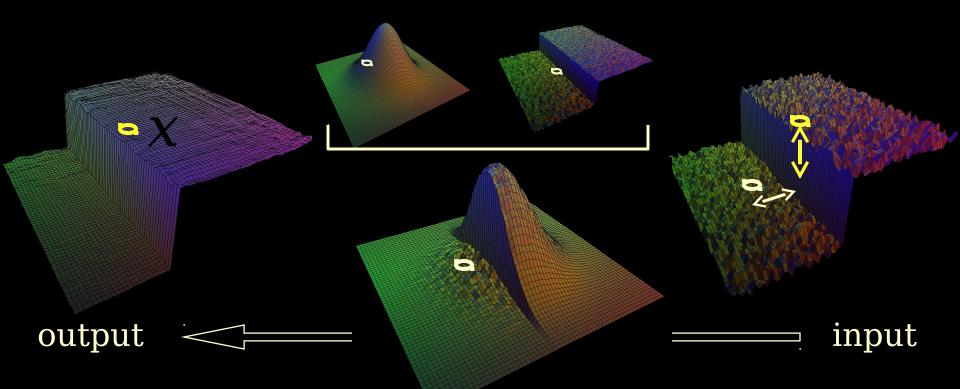
Spatial Gaussian f



Bilateral filtering

[Tomasi and Manduchi 1998]

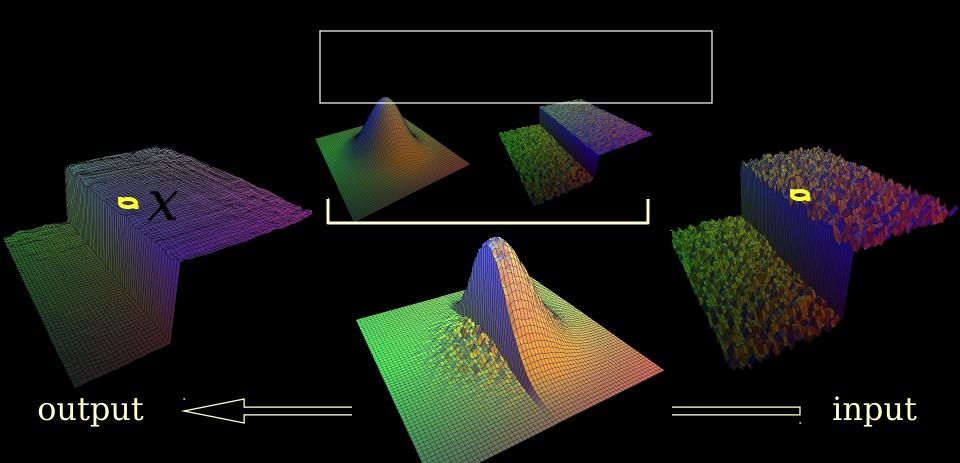
- Spatial Gaussian f
- Gaussian g on the intensity difference



Normalization factor

[Tomasi and Manduchi 1998]

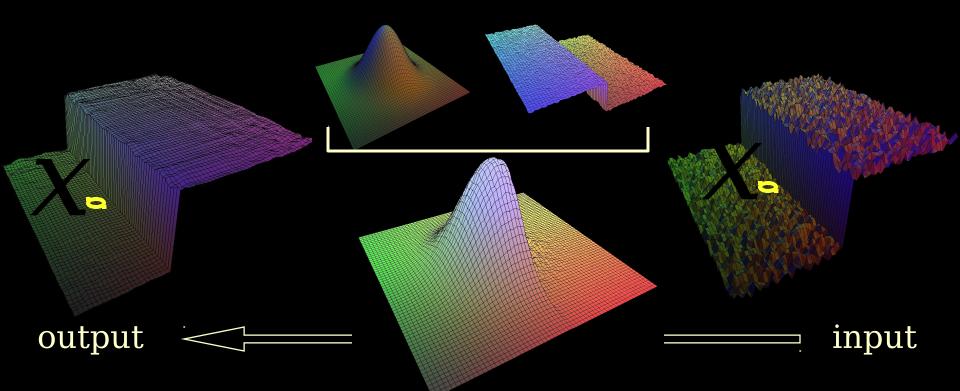
• k(x) =



Bilateral filtering is non-

Tipmes and Manduchi 1998]

• The weights are different for each output pixel



Plan

- Review of bilateral filtering [Tomasi and Manduchi 1998]
- Theoretical framework
- Acceleration
- Handling uncertainty
- Use for contrast reduction

Theoretical framework

- Framework of robust statistics
 - Output = estimator at each pixel
 - Less influence to outliers (because of g)
- Unification with anisotropic diffusion
 - Mostly equivalent
 - Some differences
- Details and other insights in paper

Spatial support



Spatial support

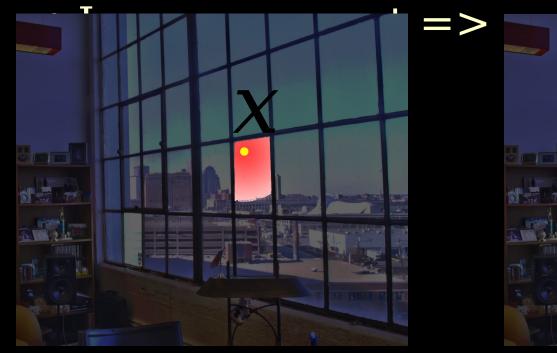
 Anisotropic diffusion cannot diffuse across edges



upport of anisotropic diffusion

Spatial support

- Anisotropic diffusion cannot diffuse across edges
- Bilateral filtering can

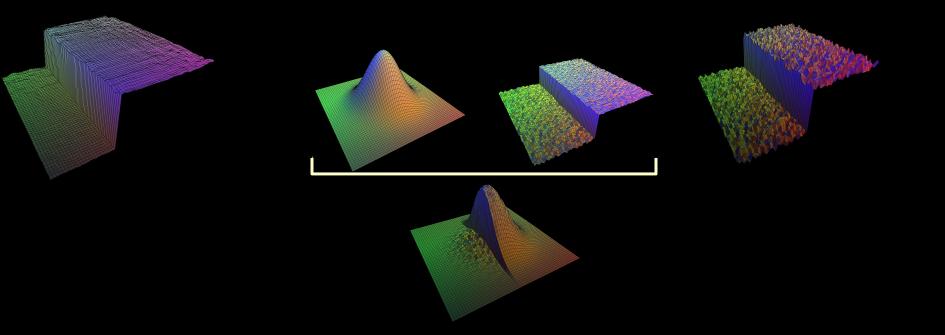




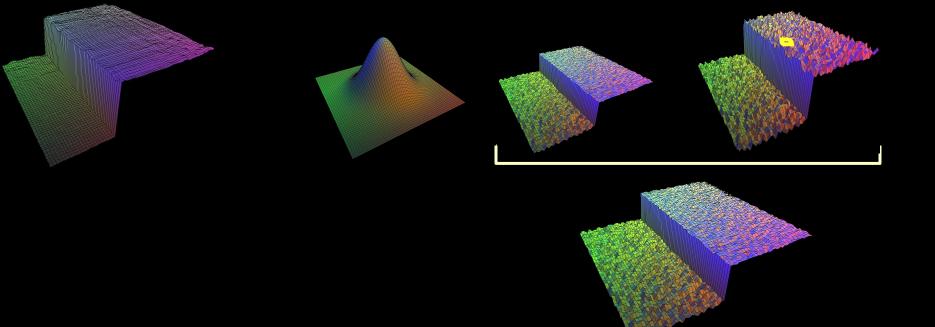
upport of anisotropic diffusion

Support of bilateral

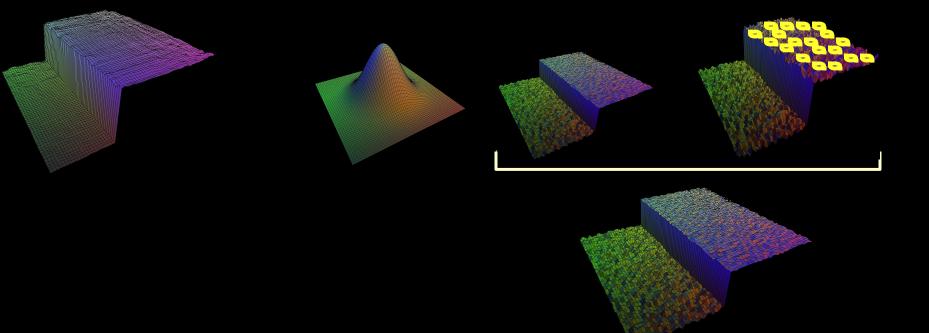
Non-linear because of g



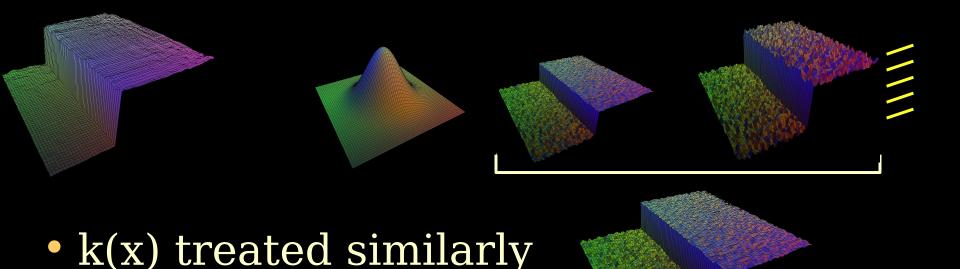
- Linear for a given value of I(x)
- Convolution of g I by Gaussian f



- Linear for a given value of I(x)
- Convolution of g I by Gaussian f
- Valid for all x with same value I(x)



- Discretize the set of possible I(x)
- Perform linear Gaussian blur (FFT)
- Linear interpolation in between



- Piecewise-linearization
 - x10 for a 80pixel kernel on 576*768 image
- Subsampling
 - x30 for a 4x subsampling
 - Superlinear because of cache

• 2 seconds for 2MPixel images (for he complete tone majes)



Handling uncertainty

- Sometimes, not enough "similar" pixels
- Happens for specular highlights
- Can be detected using normalization



eights with high uncertainty

Uncertainty

Contrast reduction



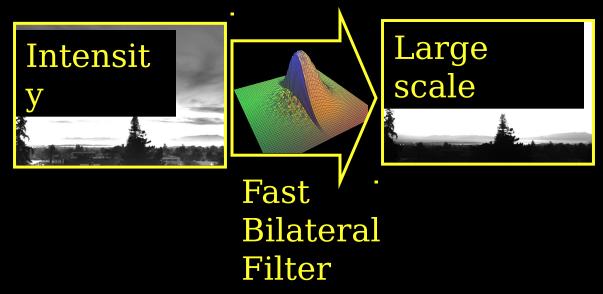
Contrast too high!





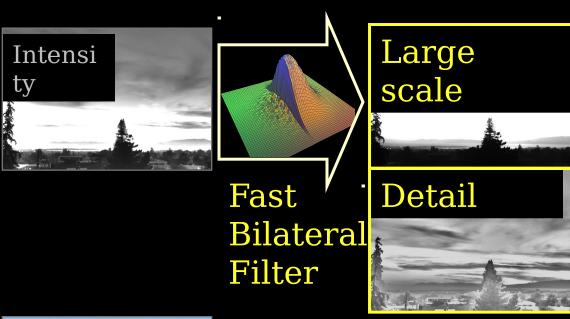








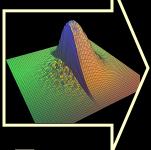


















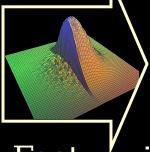


Large scale









Fast ' ' Bilateral Filter





Reduc e contra st Preserv

e!

Large scale

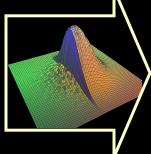












Fast
Bilateral
Filter





Reduc
e
contra
st
Preserv
e!

Large scale





Colo

Live demo

Xx GHz Pentium Whatever PC



Conclusions

- Edge-preserving filter
- Framework of robust statistics
- Acceleration (x300)
- Handling uncertainty
- Contrast reduction
- Can handle challenging photography issues
- Richer sensor + post-processing

Future work

- Uncertainty fix
- Other applications of bilateral filter (meshes, MCRT)
- Video sequences
- High-dynamic-range sensors
- Other pictorial techniques

Acknowledgments

- Mok Oh
- Ray Jones
- Paul Debeve
- Jack Tumbli
- Reviewers
- NSF
- Pixar







Gradient domain [Fattal et al.] [Durand et al.]

Bilateral

Photographic [Reinhard et al.]



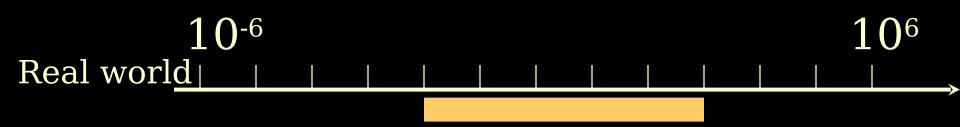
Gradient domain

Bilateral

Photographic [Fattal et al.] [Durand et al.] [Reinhard et al.]

Real world dynamic range

- $\sim 10^{-6} \text{ to } 10^{6} \text{ cd/m}^{2}$
- Often 1 : 100,000 in a scene



High dynamic range

Picture dynamic range

- Typically 1:50
 Black is ~ 50x darker that nite
- Max 1:500





<u> High-dynamic-range (HDR)</u>

ing grages



• Multiple exposure photo [Debevec & Malik

19971





Recover response curve

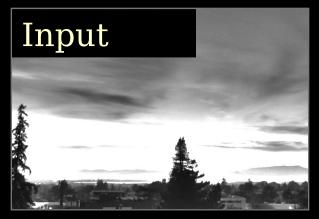
HDR value for each pixel

HDR sensors



Edge-preserving filtering

Blur, but not across edges







- Anisotropic diffusion [Perona & Malik 90]
 - Blurring as heat flow
 - LCIS [Tumblin & Turk]
- Bilateral filtering [Tomasi & Manduci, 98]



Gradient-space

Bilateral [Fattal et al.] [Durand et al.]

Photographic [Reinhard et al.]



Gradient-space

Bilateral [Fattal et al.] [Durand et al.]

Photographic [Reinhard et al.]